

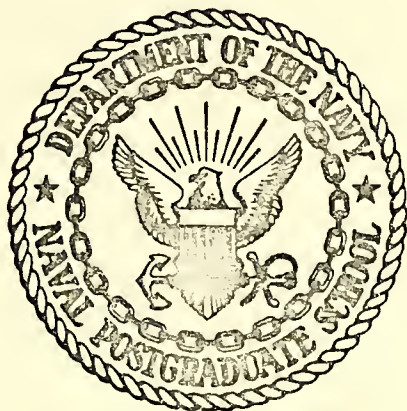
AN INVESTIGATION OF SELECTION METHODS
FOR A SIMPLE
PROGRAM FLOW ANALYSIS ALGORITHM

Norbert Lukasczyk

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THESIS

AN INVESTIGATION OF SELECTION METHODS
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PROGRAM FLOW ANALYSIS ALGORITHM

by

Norbert Lukasczyk

June 1974

Thesis Advisor:

G. A. Kildall

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An Investigation of Selection Methods
for a simple
Program Flow Analysis Algorithm

by

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requirements for the degree of

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ABSTRACT

The problem of code optimization during compilation can be approached in different ways. Kildall[6] conducted an analysis of the program structure to produce optimized object code during compilation. He utilized a directed graph to represent the program flow, along with an "optimizing function," an "optimizing pool," and a "meet operation." Based on these concepts, his program flow analysis algorithm collected corresponding graph elements on an "investigation list" and processed then those elements one at a time. The algorithm, as presented, does not specify a sequence in which these elements are selected from the list. This thesis investigates four selection methods: "Last In First Out," "First In First Out," "Steepest Descent," and "Depth First Search," a method developed by Ullman[3]. The convergence rate of the methods is evaluated by comparing the number of applications of the meet and optimizing operations in a simulated optimizing environment.

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I. INTRODUCTION

A particular problem with mechanical translation of high level languages into machine code is that more efficient code can often be written by an assembly level programmer, where efficiency is measured in the execution time for the program and the amount of memory required. The necessity to overcome this shortcoming created the science of code optimization.

The goal of code optimization is to modify the representation of a given program P into a machine code presenting a program P' such that the program P' will perform the same function as program P, but is more efficient, using less execution time, smaller storage, or fewer registers.

One global optimizing technique called interval analysis [2] partitions the flow graph into subgraphs called intervals. Each interval then is replaced by a single node containing the local optimizing information. The resulting graph is partitioned into subgraphs again, and the corresponding intervals are replaced by nodes. The definition of such interval partitions is done until the graph becomes a single node itself, at which time global information is propagated locally by reversing the reduction process.

Hecht and Ullman [2] presented a simple "bit propagation algorithm" which uses a special ordering of nodes (explained in section III-D) for a reducible graph, where a reducible graph is one which can be reduced by the interval approach from the initial flow graph to the limit flow graph of a single node with no edges. In their approach each node has an associated bit vector containing the optimizing data. This bit vector is updated during the reduction of the graph to the final solution.

Another approach is done by Kildall [6]. He conducts the analysis using a program flow analysis algorithm, which propagates information along the program flow until all required information is collected. This algorithm is reviewed in section III-B. The algorithm, as presented, does not specify the sequence in which the basic blocks are processed. This thesis will investigate some selection methods which specify the sequences in which the basic blocks are processed. These selection methods are simulated and compared with respect to the convergence rate of the algorithm.

II. BACKGROUND

A. DEFINITIONS

Before reviewing the algorithm[6] it is necessary to define the following terms.

A directed graph is a two tuple $GD = (N, A)$, where "N" is a finite set of nodes and "A" is a subset of $N \times N$, called "arcs." The arc (X, Y) leaves node X and enters node Y. Node X is called a predecessor of node Y and node Y is called a successor of node X.

A path from node B to node C in GD, for B, C in N is a sequence of nodes (X_1, X_2, \dots, X_k) such that $X_1 = B$ and $X_k = C$ and (X_i, X_{i+1}) is an arc in A for all $i, 1 \leq i \leq k-1$.

The length of a path is one less than the number of nodes in the sequence ($k-1$ in the above case). If C equals B the path is called a cycle.

A program flow graph is a triple $G = (N, A, E)$ where N and A are as defined above and where E is a subset of N and contains the "entry node(s)," such that given a node n in N there exists a path (X_1, X_2, \dots, X_k) where X_1 is in E and X_k equals n.

An optimizing pool associated with each node in the graph is a set describing the optimizing information associated with the particular node in terms of the analysis being conducted. For example this set may contain subexpressions as elements, register allocation information, or propagated constant values.

An input pool is the set of optimizing information elements entering a node.

An output pool is the set of optimizing information

elements leaving a node.

A meet operation is defined which combines two or more pools at a node, where two or more program paths join. The form of the meet operation varies with the type of analysis. Formally, the meet operation, denoted by " \wedge ", is a binary operator which maps $P \times P$ into P , where P is the set of all optimizing pools. The meet operator has the following properties:

For a, b, c in P

$$a \wedge a = a \quad (\text{idempotent})$$

$$a \wedge b = b \wedge a \quad (\text{commutative})$$

$$a \wedge (b \wedge c) = (a \wedge b) \wedge c \quad (\text{associative})$$

The meet operation permits the definition of a partial ordering on the optimizing elements :

$$a \geq b \text{ iff } a \wedge b = b.$$

To simplify the notation, the form

$$\bigwedge_{1 \leq i \leq k} x_i \text{ is defined as } x_1 \wedge x_2 \dots \wedge x_k.$$

An optimizing function f maps a given input optimizing pool to the output pool of the corresponding node which contributes to the input pools of the node's immediate successors. The function differs with the type of analysis being conducted. The function, however, must satisfy the following homomorphism condition for Kildall's data flow analysis algorithm to be applicable :

$$f(n, a \wedge b) = f(n, a) \wedge f(n, b)$$

for all nodes n in N , and a, b in P .

A zero element 0 is an element of P satisfying the conditions

$$0 \wedge x = 0 \text{ for all } x \text{ in } P.$$

A one element 1 is an element of P satisfying the condition

$$1^A X = X \text{ for all } X \text{ in } P .$$

B. REVIEW OF KILDALL'S ALGORITHM

Kildall's program flow analysis algorithm is used in order to perform compile time optimization of object code. Although the algorithm is optimization independent several different useful optimization functions have been applied, such as locating redundant computations or register operations. In the following paragraphs this algorithm will be reviewed, and later will be illustrated by an example of common subexpression analysis. The algorithm can be described in the following way :

STEP 1: Initialize an investigation list "L" by the entry nodes of the program graph along with the corresponding optimizing pools "OP." Normally there is only one entry node and its optimizing pool is empty (initialized to the zero element).

STEP 2: If the list "L" is empty then halt. All nodes of the graph have been processed (at least once) and the optimizing pools are in their final state.

STEP 3: Otherwise, select a node "X" from "L" with its corresponding (already established) optimizing pool. When the node is processed the first time, assume the approximate pool to be initialized to the 1 element.

STEP 4: Use the meet operator to combine the already existing optimizing pool with the input pool "IP" incoming from the immediate predecessor. Assume the result as the new optimizing pool. If the result does not change the existing optimizing pool go to "STEP 2."

STEP 5: Otherwise map the result to a new output pool with the corresponding optimizing function. Enter all immediate successors into "L" with the output pool of X as a new input pool.

STEP 6: Go to STEP 2. In general the algorithm is stated as

A1 [Initialize] $L \leftarrow \{(e, \underline{0}) \mid e \text{ in } E\}$

A2 [Terminate ?] If $L = \emptyset$ then halt

A3 [Select a node] Let L' be an element of L ,
 $L' = (X, IP)$ for some X in N
 and IP in P , where P is the set of all
 possible optimizing pools, then set
 $L = L - \{L'\}$

A4 [Traverse?] Let OP be the current pool
 of optimizing information associated
 with the node X (initially $OP = \underline{1}$)
 If $OP \leq IP$ go to STEP A2, where IP is
 the incoming pool.

A5 [Set pool] $OP \leftarrow OP \cap IP$
 $L = L \cup \{(Y_i, f(X, OP)) \mid Y_i \text{ in } I(X),$
 where $I(X)$ is the set of all
 immediate successors of X . }

A6 [Loop] Go to STEP A2

As an illustration of the algorithm, consider the problem of common subexpression elimination. In this case the "pools" are sets partitioned into equivalence classes. Such equivalence classes contain previously computed expressions which are known to have identical values. The meet operation is defined as intersection of equivalence

classes, and the "optimizing function" builds new equivalence classes of expressions which are known to have the same value, or it adds expressions to already existing classes. As an example consider the following skeletal program:

```

      z := y
1 : r := k * y
      x := k
      if c = 1 go to 2
      y := z
      r := u * z
      x := u
      if 1 ≤ c go to 1
2 : u * z
      x * y

```

Neglecting the if statements, the resulting program flow graph is presented in Figure 1, where the nodes A,B,C,D,E,F represent basic blocks which are segments of the program containing no transfers of the program control into or out of the segment and where the edges represent the program flow.

The program flow graph given in Figure 1 is processed in the following tabular form :

Column "STEP" contains the number of nodes already processed.

Column "NODE" contains the node being processed.

Column "INPUT POOL" contains the current approximation to the final optimizing pool.

Column "OUTPUT POOL" contains the output pool formed by the optimizing function which will be the input pool for the immediate successor listed in column L.

The single equivalence classes are separated by a vertical bar, and the single elements of a class are separated by a comma. The analysis is given in Table 1. The optimizing pools associated with the underlined nodes are the final pools.

The result of this analysis is as follows. The first

expression at node D is $Y := Z$. Referring to the input pool

$$IP_{(D)} = \{z, y | k, x, |r, k*y, x*y\}$$

there already exists an equivalence class " $|z, y|$ " and therefore it would be redundant to produce code again for this assignment. A similar result is found by the algorithm at node F. The expression $X * Y$ is already a member of the input pool

$$IP_{(F)} = \{z, y | x | u | k | r, x*y | u*z | k*y\}$$

and thus it is not necessary to recompute the expression.

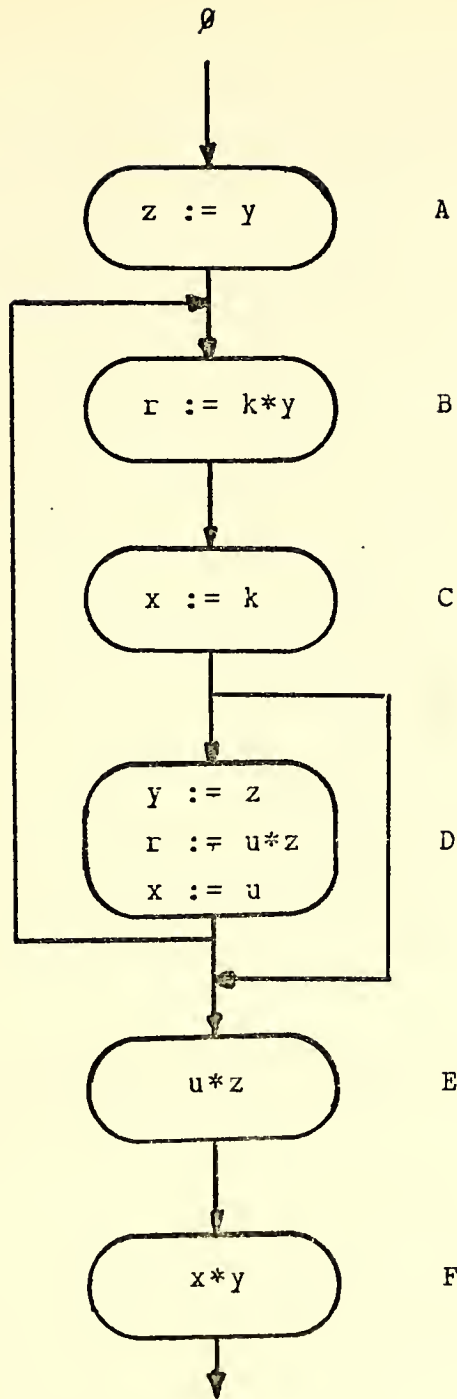


FIGURE 1.
Example for a program flow graph

TABLE 1
Common Subexpression Elimination Analysis

STEP	NODE	INPUT POOL	OUTPUT POOL	L
1			\emptyset	A
2	<u>A</u>	\emptyset	z, y	B
3	<u>E</u>	z, y	$z, y r, k*y, k*z k$	C
4	<u>C</u>	$z, y r, k*y k$	$z, y k, x r, k*x, x*y, x*z$	D, E
5	<u>E</u>	$z, y k, x r, k*y, x*y$	$z, y k, x u r, k*y, x*y u*z$	F
6	<u>F</u>	$z, y k, x u r, k*y, x*y u*z$	$z, y k, x u r, k*y, x*y u*z$	-
7	<u>D</u>	$z, y k, x r, k*y, x*y$	$z, y x, u r, u*z, x*y k*y k$	E, B
8	<u>E</u>	$z, y x r, x*y k*y k$	$z, y x u k r, x*y u*z k*y$	F
9	<u>F</u>	$z, y x u k r, x*y, u*z k*y$	$z, y x u k r, x*y u*z k*y$	-

Note: only expressions or subexpression which occur in the graph are propagated.

III. SELECTION METHODS

The choice of the node from the investigation list in step 3 of Kildall's algorithm is arbitrary, as shown in Ref[6]. This fact has motivated the investigation of the effect of some selection methods on the convergence rate of the algorithm.

In the analysis of the previous example of common subexpression elimination presented in Table 1, there was a choice of nodes at step 4. Instead of node E the node D could have been taken. Proceeding with the choice D instead of E reduces the number of steps leading to the final solution from nine to seven, as shown in Table 2.

A. LAST IN FIRST OUT (LIFO)

Representing the investigation list in form of a horizontal stack suggests a selection method which always processes the top of the stack, assumed to be the "right end." Due to step 5 of the algorithm, the currently processed node enters all its immediate successors at the stack top. The actions of the algorithm are most easily seen through a simple example. Considering the skeletal flow graph given in Figure 2, stack order processing produces the following states of column L. Processing the entry node A results in:

$$L_1 = B C D.$$

Processing node D results in

$$L_2 = B C I J.$$

Selecting J produces

$$L_3 = B C I L M.$$

TABLE 2
Common Subexpression Elimination Analysis
Improved version

STEP	NODE	INPUT POOL	OUTPUT POOL	L
1			\emptyset	A
2	<u>A</u>	\emptyset	$z, y,$	B
3	<u>E</u>	z, y	$z, y r, k * y, k * z k$	C
4	<u>C</u>	$z, y r, k * y k$	$z, y k, x r, k * x, x * y, x * z$	D, E
5	<u>D</u>	$z, y k, x r, k * y, x * y$	$z, y x, u r, u * z, x * y k * y k$	E, B
6	<u>E</u>	$z, y x r, x * y k * y k$	$z, y x u k r, x * y u * z k * y$	F
7	<u>F</u>	$z, y x u k r, x * y, u * z k * y$	$z, y x u k r, x * y u * z k * y$	-

Note: only expressions or subexpression which occur in the graph are propagated.

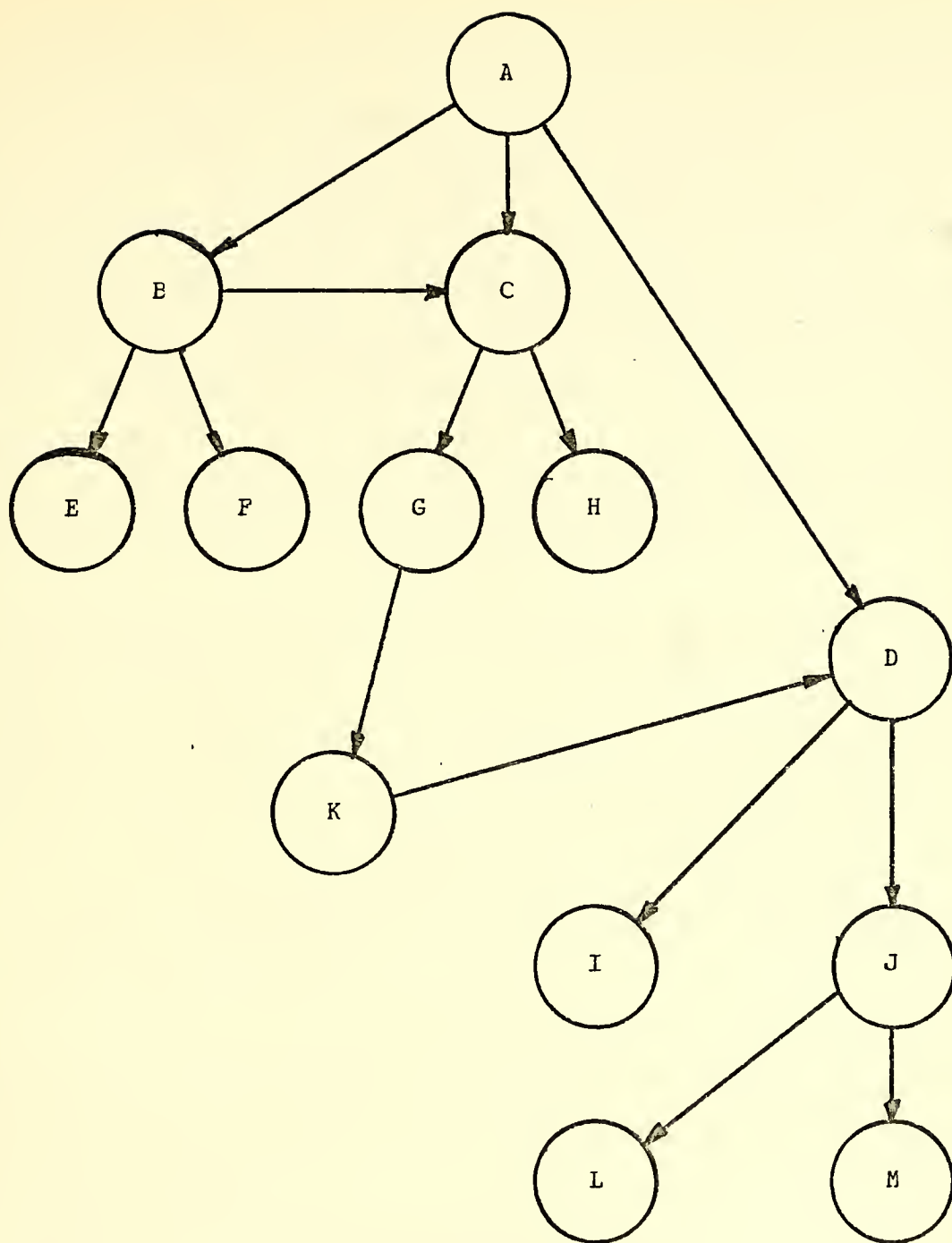


FIGURE 2.
Flow graph example for
LIFO and FIFO node selection

Since node L and M have no successors, the subtree rooted in D is processed. The optimizing pools (OP) for the nodes I, J, L, M are of the form:

$$OP_{(n)} = \bigwedge_{D \rightarrow n} f(OP_D) \text{ for } n = I, J, L, M$$

where OP_D is the result produced by the meet operation along the path from node A to node D, and $D \rightarrow n$ is a path from D to n. The next node being processed is node C, and therefore the list will be of the form

$$L_4 = B G H.$$

Since H has no successors the node G is processed leading to K which, in turn, is immediately processed.

$$L_5 = B K.$$

Assuming that the output pool of node K will change the OP_D , the whole subtree rooted in D has to be reentered and processed again as shown in L_1 to L_3 . The optimizing pools of the nodes G, H, D, I, J, L, M are then of the form:

$$OP_{(n)} = \bigwedge_{C \rightarrow n} f(OP_C) \text{ for } n = G, H, D, I, J, L, M.$$

After reprocessing the nodes, B is processed which results in the list:

$$L_9 = E F C.$$

Assuming again that the output pool of B changes OP_C , the subtrees rooted in C and D have to be reentered and processed again.

$$L_{10} = E F G H$$

$$L_{11} = E F K$$

$$L_{12} = E F D$$

$$L_{13} = E F I J$$

$$L_{14} = E F I L M.$$

After doing so, the optimizing pools for the nodes represented by n are:

$$OP_{(n)} = \bigwedge_{B \rightarrow n} f(OP_B)$$

for n = E, F, C, G, H, K, D, I, J, L, M.

Since node E and node F have no successors, the stack is empty after processing each element and the algorithm stops.

An obvious disadvantage was to start at the right side of the stack, but the graph given in Figure 2 is, of course, only one of many. There might be graphs for which this method is more efficient. For example, if one turns the given graph from left to right the entering sequence will then be D C E. In this case, the algorithm converges more rapidly.

To describe the relations between the nodes by more associative names, call the successors "sons," the sons of a father "brothers," and consider the immediate successors of corresponding brothers to be on one "level." For example, the node A is the father of B C D and the nodes E F G H I J are on one level. The selection method described above propagated the optimizing information along a path connecting sons of succeeding levels in "top to the bottom," or "depth first" fashion. The disadvantage is that all optimizing information entering nodes on this path, coming from nodes of upper levels but being located at the left side of the stack, is disregarded. Assuming that the incoming pool will change the optimizing pool of the entered node, the whole path following the entered node has to be processed again, as illustrated in the case of the subtree rooted in D when node K or B was processed.

B. FIRST IN FIRST OUT (FIFO)

Based upon the analysis presented in the last section the method presented here selects the nodes in a horizontal direction instead of a depth first sequence. That is at

first all nodes of one level are processed, followed by their successors, again all those of one level, and so on.

Considering the same stack model, the nodes are taken now from the left side, and the node which enters first will also be processed first. Processing the graph of Figure 2 results in the following investigation lists. The node A will produce the list

$$L_1 = B C D.$$

B will then be selected. Processing the node B will enlarge the list to

$$L_2 = C D E F C.$$

The node C is entered twice into the list and is distinguished by the associated optimizing pools. Node A caused its successor C with the approximate optimizing pool

$$OP_C = \bigwedge_A f(OP_A).$$

Node B on the other hand, enters the successor C with the pool

$$OP_C = \bigwedge_B f(OP_B).$$

The following change is made to improve the algorithm in later steps. Instead of adding the corresponding successors in step 5 of the algorithm, the "union" is formed of the existing list L and the set of successors. For those nodes already on the list, the meet operator is applied to combine the different incoming pools.

It is possible to use the union operation since the character of the investigation list is one of a "waiting list" indicating those nodes which remain to be processed. It is easily shown that as long as the input pool is updated by the meet operation it is not necessary to enter a node again. Using this change in step 5 reduces the number of optimizing function applications by the number of times the node is not additionally entered.

Processing the algorithm in this way using the union operation results in

$L_3 = D E F G H$

$L_4 = E F G H I J$

$L_5 = H I J K$

$L_6 = K L M$

$L_7 = L M D$

$L_8 = I J$

$L_9 = L M.$

After processing these nodes the list is empty and the algorithm stops.

Assuming the same relation of the optimizing pools to one other as in section III-A one improvement can already be noticed: the nodes M and L are processed only twice.

C. STEEPEST DESCENT

The two methods presented in the previous section only considered the sequence of the nodes based upon the relationship father, son, or brother. The third method presented now will take into account the properties of the associated optimizing pool of each node waiting on the investigation list. Kildall[6] suggests a method called "steepest descent" which considers the size of the pool in obtaining a selection sequence of nodes with the intention of decreasing the pool size as quickly as possible.

The general character of the meet operator is similar to that of an intersection operator: that is, in the case of common subexpression elimination, it maps the incoming pools into a new optimizing pool for the corresponding node. This implies that the size of the produced optimizing pool is always less than or equal to the former one. Therefore, processing the node with the smallest pool available on the investigation list first will map the corresponding

successors' pools into a form which is closer to the final state.

To illustrate this method consider the shortest path problem (Ref.[1]). In the graph given in Figure 3, each node has a distance associated with it represented by a number. The approximated optimizing pool is the sum of distances along a traveled path beginning at the entry node up to the currently processed one. The meet operator will choose the smallest incoming value as the new optimizing pool. The optimizing function will add the associated distance of the node to its optimizing pool to form the output pool which is passed to the successors. The term "smallest" in this example is related to the sum represented by the optimizing pool.

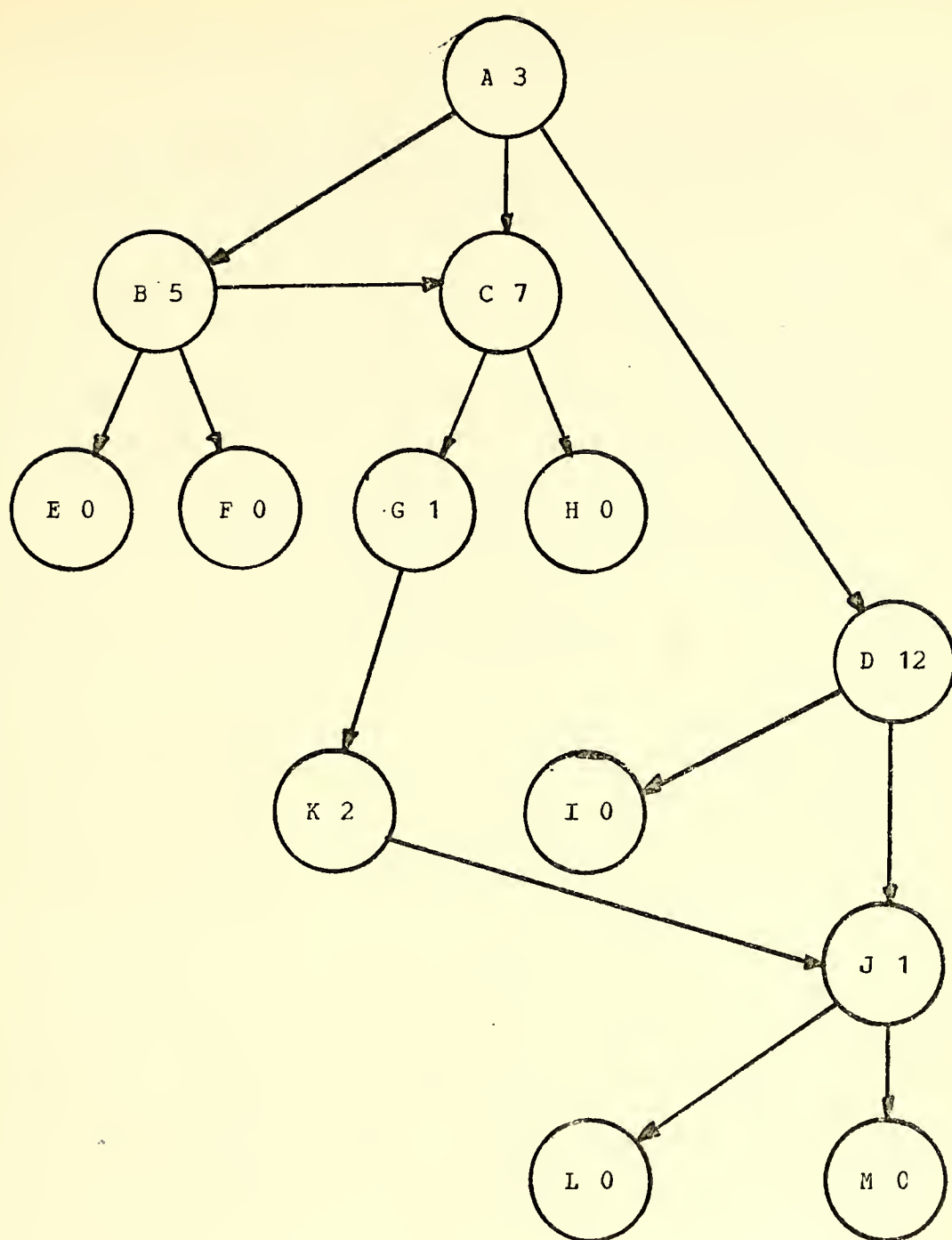


FIGURE 3.
Flow Graph Example for
Steepest descent

Processing the node A will produce the list

$$L_1 = B(3), C(3), D(3).$$

Since all optimizing pools are equal node B is arbitrarily processed next, and the new list is

$$L_2 = C(3), D(3), E(8), F(8).$$

Selecting C(3)

$$L_3 = D(3), E(8), F(8), G(10), H(10).$$

Selecting D(3)

$$L_4 = E(8), F(8), G(10), H(10), I(15), J(15).$$

Selecting E(8), F(8), G(10)

$$L_5 = H(10), I(15), J(15), K(11).$$

Selecting H(10), then K(11) resulting in

$$L_6 = I(15), J(13).$$

Note that the optimizing pool at node J had the value 15 for an optimizing pool. The incoming pool was of value 13 and, due to the meet operator the smaller value was taken as the new optimizing pool. Applying the steepest descent method, node J is taken and

$$L_7 = I(15), L(14), M(14).$$

According to this method, the sequence of selection is L(14), M(14), I(15). Compared to the methods presented previously, the nodes M and L are processed only once which is a further improvement. The change in the graph does not influence the number of traversals of node L and node M.

D. DEPTH FIRST SEARCH

One consequence of the methods presented in section III-A and III-B was the importance of the processing sequence of the nodes along the possible paths. The relations father - son and brother - brother were considered in determining the best sequence. Another approach will be to preprocess the graph in order to find the relations between all nodes of the graph to each other in the sense of a family tree. The nodes will then be selected in a sequence conforming to the family hierarchy.

This idea has been implemented by Hecht and Ullman[2]. Kam and Ullman[3] combined this ordering process with Kildall's flow graph algorithm. This combination will be presented as the fourth selection method.

The ordering of the nodes of a flow graph G corresponds to the dominance relation and is the reverse of the order in which a node is last visited while growing any depth first spanning tree of G .

A depth first spanning tree (DFST) of a flow graph is defined as a directed rooted ordered spanning tree grown by the algorithm which is described below:

[D1 Initialization] The root of the DFST is the initial node of G . Let this node be the node " m " which is visited in step D2. The variable " i " will be used to number the nodes in "rEndorder." Initially $i < K$, where K is the number of nodes in the graph.

[D2 Visit node m] If node m has a successor X not already on the DFST, select X as the right most son of m found so far on the spanning tree. If this step is successful, node X becomes the node m to be visited next by repeating step D2, otherwise

[D3 Label] Let m be the node being visited. Let $rEndorder \leftarrow i$, and $i \leftarrow i-1$, if m is the root then halt, otherwise execute step D2 using the father of m . An example of this algorithm is illustrated in Figure 4.

The optimizing pools of the corresponding nodes are processed then in a sequence determined in the following way.

Kam and Ullmann use an array A , equivalent to the investigation list L , a pointer j , and a boolean switch called "change." They initialize the optimizing pool of the entry node $A[1]$ by the 0 element and proceed by the following steps :

STEP 1 for $j := 2$ step 1 until k do

$A[j] := \bigwedge_{d \in I(j)} f_d(A[d]);$

where $I(j) = \{d \mid d \text{ is an immediate predecessor of } j \text{ and } d \text{ is less than } j\}$

change := true;

while change do

Comment this while statement is

equivalent to the step 2 of Kildall's algorithm:

if L is empty then halt;

begin

change := false;

STEP 2 for $j := 2$ step 1 until k do

begin

temp := $\bigwedge_{d \in I(j)} f_d(A[d]);$

where $I(j) = \{d \mid d \text{ is an immediate predecessor of } j\}$


```
if temp ≠ A[j] then change := true;  
A[j] := temp;  
end;  
End of while;
```

Step two is equivalent to step four in Kildall's algorithm. A change of the optimizing pool of the currently processed node will cause a new iteration of the while statement which means a reprocessing of the node. This is accomplished by entering the node onto the investigation list again.

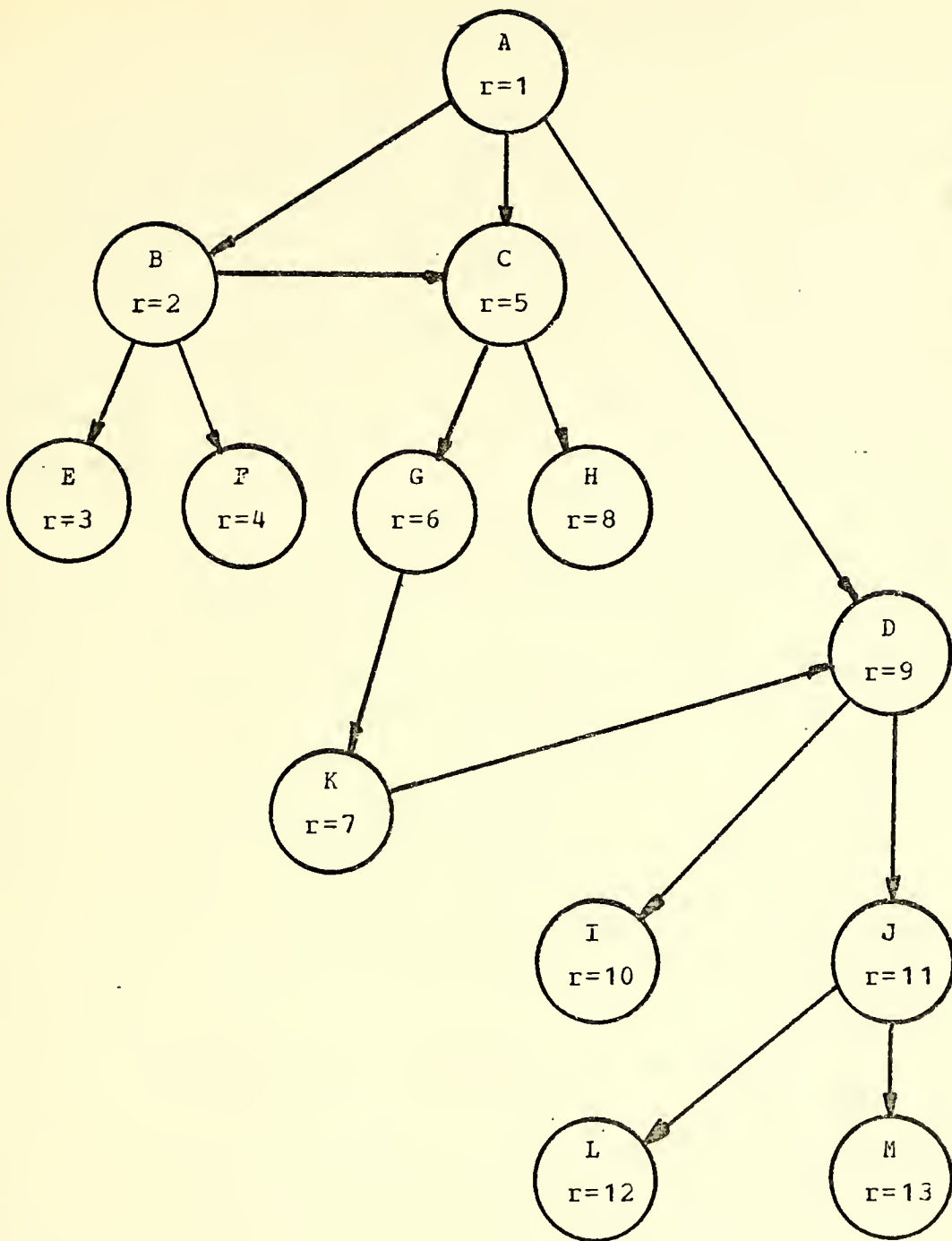


FIGURE 4.
Example for Ullman's Ordering Algorithm

IV. IMPLEMENTATION OF THE SELECTION METHODS IN A SIMULATION

This section presents a simulation model for the purpose of evaluating the convergence rate of the various node selection methods. The model is based upon a randomly generated flow graph. The instructions attached to a node are represented by distances along the arc leading from a node to its successors. The optimizing pool in this model represents the sum of the arc lengths along the possible paths starting with the entry node up to the currently processed node. In this case the goal of the algorithm is to decrease the pool size in order to minimize the distance sum. This is done by searching along the possible paths to find the smallest sum.

The relation father - son and the associated arc length represented by the three tuple (NX,NY,NZ) is determined by a uniform random number generator[7]. To obtain the connectivity of the graph, the new father for the next level of successors is selected from the last group of sons.

The optimizing function maps the optimizing pool of the corresponding node into the output pool passed to the successors by adding the corresponding arc length NX to the optimizing pool:

$$\text{Output pool} = \text{Optimizing pool} + \text{NX}$$

In the general code optimization problem the optimizing function is applied only once when processing the node since the produced output pool is valid for all successors. In the model, however, the output pool differs due to the different arc lengths along the connections. To overcome this shortcoming of the model, all applications to compute the different output pools during processing the node are counted only as one application. This is accomplished by incrementing the "function tally" (a counter explained in section V) each time the corresponding node is processed.

The meet operator compares the incoming pool with the current optimizing pool and sets the new optimizing pool to the smaller of the two. If the old optimizing pool is substituted by a smaller one, the node will be entered into the investigation list if it does not already exist on the list. The list tally (counter explained in section V) is also incremented.

Due to the linear form of the optimizing function in the shortest path problem, the value of the optimizing pool is constantly increasing along a path. Therefore, each loop is only propagated once, except when additional paths lead to the loop entry, because the optimizing pool value at the end of the loop is always greater than or equal to the value at the beginning of the loop.

To make the simulation model closer to an actual program flow graph process, a second run will be made with the non-linear optimizing function

$$\text{Output pool} = \frac{OP^2}{NX} + \frac{OP}{NY} + NZ$$

where NX, NY, NZ are randomly generated coefficients attached to each arc. In this case, it is possible that the function value output is less than the incoming value OP. Therefore, the value at the end of a loop can be less than the value at the beginning and can cause additional traversals of the loop.

The nonlinear optimizing function can be used, since the homomorphism condition is satisfied, which is shown in appendix A.

V. EVALUATION CONCEPT

The final optimizing pool associated with each node upon termination of the algorithm is uniquely determined, independent of the order of choice, which is shown in Ref[6]. Thus, the number of steps leading to the final solution might be a measure of the convergence rate. Kildall[6] defined the upper bound on the number of steps for the given algorithm (section II-B) as follows:

Let n be the cardinality of N and $h(OP)$ be a function of OP (which in turn may be a function of n) providing the maximum length of any chain between 1 and 0 in OP . Step 5 of Kildall's algorithm can be executed a maximum of $h(OP)$ times for any given node. Since there are n nodes in the program graph, step 5 can be performed no more than $n * h(OP)$ times.

This upper bound on the number of steps is a theoretical one, and in actual practice the number of steps to a solution might be far less than that.

Ullman[3] proposed the number of iterations of the algorithm described in section III-D as the convergence rate measure. He claimed that the algorithm will halt after at most " $d+3$ " iterations, where d is the maximum number of back edges given by any depth first spanning tree in a cycle free path.

Since the theoretical upper bound is only applicable to Kildall's algorithm, and the number of iterations is only applicable to Ullman's method these criteria are not uniformly meaningful for all four methods.

The evaluation concept used in the investigation described in the following section is based upon the application of the meet operator and the optimizing function first relative to the number of nodes, and then to the number of arcs. This is uniformly meaningful since the

implementation of the function and the operator is the same in all four methods. The methods will differ, however, in the number of the applications as already mentioned in their description. Since the convergence rate of the algorithm depends upon the number of applications of the meet and optimizing function, this number will be used as the evaluation criteria later on.

To determine the number of applications of the meet operation and optimizing function, two counters are associated with each node: a "list tally" denoted by LISTTALLY and a "function tally" denoted by FUNCTALLY.

The list tally is incremented each time the optimizing pool of the corresponding node is changed by the meet operator, i.e., the node is entered into the investigation list by the union operator.

The function tally will be incremented each time the optimizing pool of the corresponding node is mapped to an output pool using the optimizing function.

To compare the effect of the methods on the algorithm convergence rate, single node counters can be compared, and to get a general overview, the counters can be summed and the total number of applications during the algorithm run can be compared.

Using this evaluation concept the effects of the methods on the convergence rate can be investigated for different kind of graphs. The graphs investigated in the following paragraphs vary in:

- the number of nodes,
- the number of leaving arcs,
- the number of generated levels,
- and the arc length representing the different type of optimizing pools.

VI. RESULTS

The effect of the node selection methods on the convergence rate of the algorithm when varying the simulation parameters is presented below.

The investigated graphs can be separated into five main groups, characterized by the number of nodes contained in the graph. The simulated graphs contained ten, twenty, thirty, forty, and fifty nodes.

Each main group is divided into four subgroups distinguished by the number of generated levels contained in the corresponding graphs. The number of generated levels being considered are ten, twenty, thirty, and fifty.

Each subgroup contains five graphs which are equal in the number of nodes and the number of levels but vary in the numbers of leaving arcs. The number of leaving arcs being considered are two, four, ten, twenty, and thirty arcs.

The computer output starting on page 46 shows the results of the simulation runs using the linear and nonlinear optimizing functions. At the end of each main group the number of times a method used the lowest number of applications during the last twenty runs is presented.

Looking at the number of applications of the meet operator and optimizing function given by the corresponding tally will show the following trends.

Increasing the value of a variable generally caused an increase in the number of applications,

Increasing the number of nodes will cause on the average an increase on the number of applications in the following manner. Using the linear optimizing function the number of applications increases linearly when the steepest descent method is applied, and exponentially when the other methods are used. This is not surprising since one can easily show that each node is visited only once in the linear case when

using the steepest descent method. Using the non-linear optimizing function, the number of applications increases linearly in all four cases. The trends can be easily seen in Figure 5 for the linear function, and in Figure 6 for the non-linear function.

The increases caused by varying the number of levels and arcs are shown in Table 3 for graphs of ten and fifty nodes. The amount of increase when varying the number of arcs and levels depends also upon the number of nodes contained in the graph. This can be explained as follows: the size of a generated flow graph is limited by the number of nodes, levels, and arcs. The maximal number of distinct nodes being entered by distinct arcs is equal to the product of the number of levels and arcs. Whenever the value of this product is greater than the number of nodes of the corresponding graph, the generated new nodes being entered are already in the graph. That is, they are successors or predecessors of other nodes as well. After a certain increase in the number of levels or leaving arcs relative to the number of nodes, only loops or parallel arcs are generated. Increasing the number of loops or number of parallel arcs has little influence on the number of applications, since the probability that a successor's optimizing pool is already in its final state and the node is not reentered again into the investigation list increases also, which saves the application of the meet operator and optimizing function.

Looking at the results of the nonlinear function the same trend is noticed, but the number of applications is higher in general due to the additional traversals of the loops.

Looking at the results with regard to the effect of the different methods, the following can be observed.

The number of applications for the meet and optimizing function in the case of the LIFO method is always equal. This is necessarily true since all nodes whose optimizing

pool was changed were entered into the list without using the union operator.

Investigating the list tally first to avoid the influence of the union operator will yield the following effects. With regard to graphs with small number of nodes and small numbers of leaving arcs the effect of the three methods LIFO, FIFO, and STEEP are similar, The number of applications of the meet operator varies only slightly. Increasing the number of levels or leaving arcs, however, the difference will be emphasized. The FIFO method used less applications than LIFO, but was outnumbered itself by the STEEP method which used the lowest number of applications in the most cases. The Ullman method is very handicapped by the "for statement" used inside the while loop. This influence became more obvious with increasing number of nodes in the investigated graphs.

The number of applications of the optimizing function depends very much on the number of meet operations, since only those nodes were considered which were on the investigation list. Therefore, when the number of meet operations decreases, the number of optimizing function applications also decreases. However, the improvement due to the union operator when entering a node into the investigation list is very obvious, since the differences between the list tally and function tally in all three methods FIFO, STEEP, and Ullmann are remarkable.

To get a general overview of the effect of the methods several runs of the same type were made with different seeds for the random number generator to provide a large number of distinct graphs. The results are shown in Table 4 using the linear function and in Table 5 using the nonlinear function. The tables contain the number of times the corresponding method used the lowest number of applications with regard to the meet and optimizing function. The summation of the corresponding numbers shows that the Steepest Descent method yields the best convergence rate.

Applications

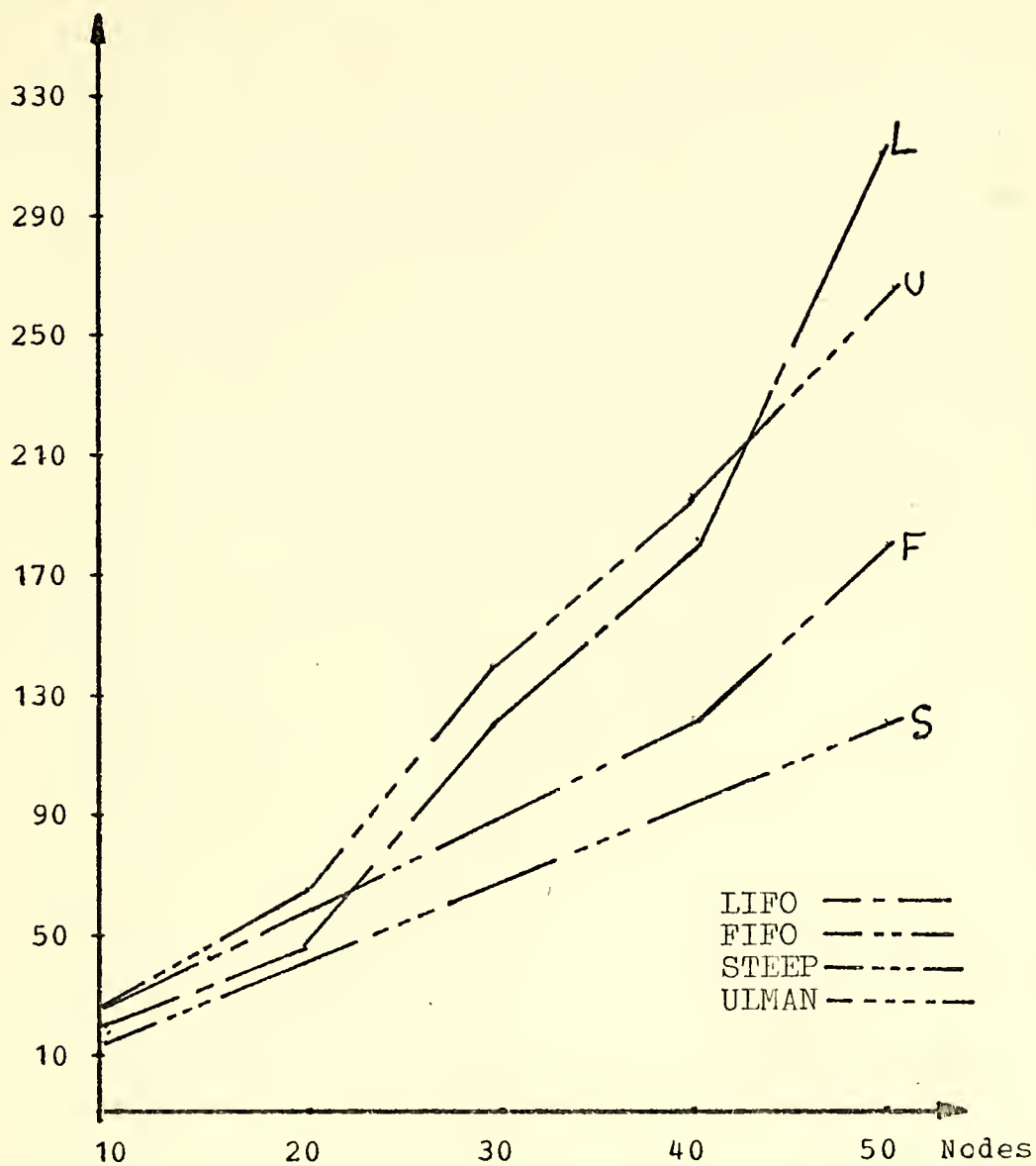


FIGURE 5.

Relation between the number of applications and
number of nodes (linear function)

Applications

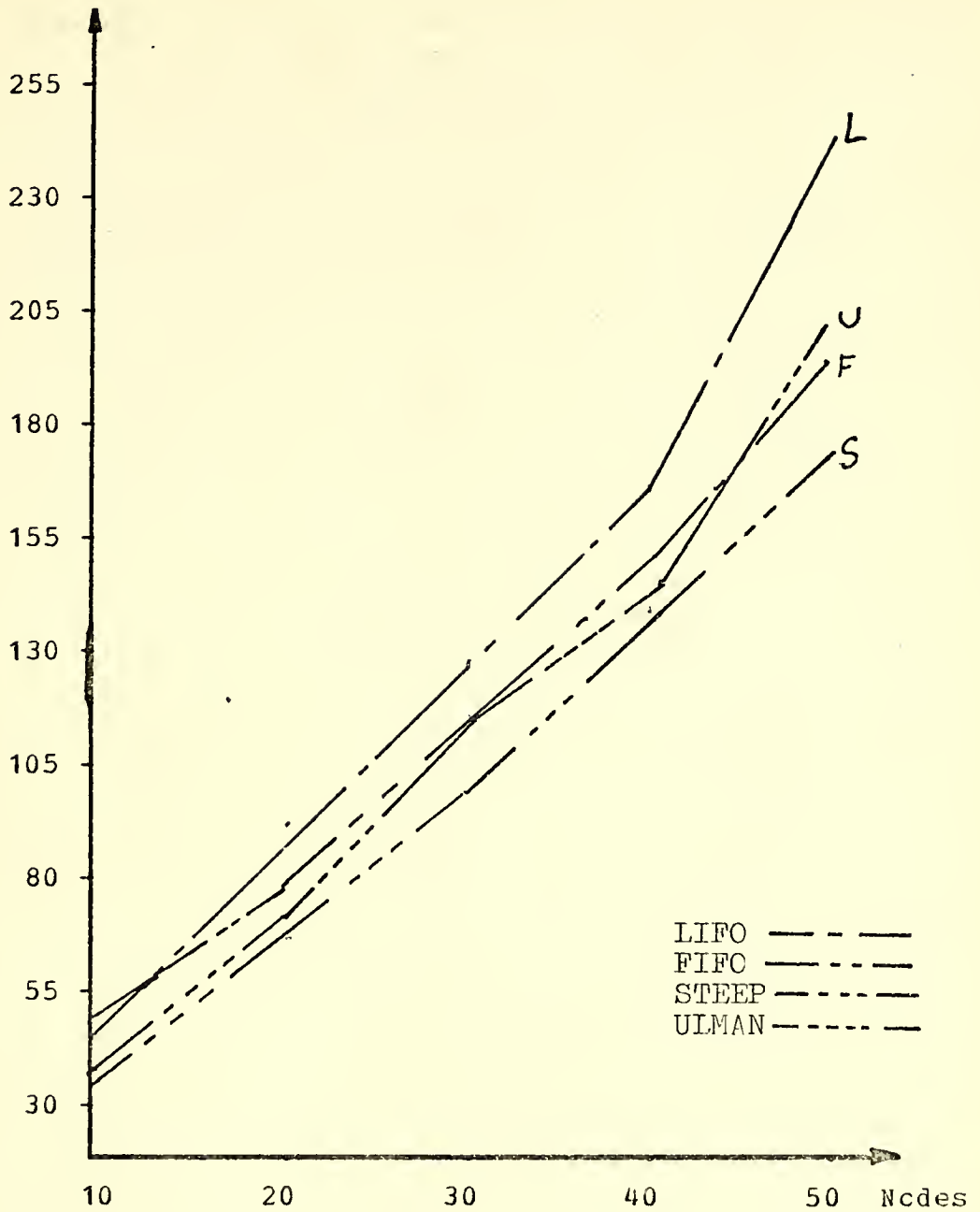


FIGURE 6.

Relation between the number of applications and
number of nodes (non-linear function)

TABLE 3
Increases Caused by Changing the Simulation Parameters

Graph of ten nodes

	level 10 arcs 2	level 50 arcs 30	increase
LIFO	11	16	5
FIFO	10	18	8
STEEP	10	16	6
ULLMAN	17	19	2

Graph of fifty nodes

LIFO	16	304	288
FIFO	16	215	199
STEEP	16	131	115
ULLMAN	31	246	215

TABLE 4
Linear Function Results

Seed	Orig		Fifo		Steep		Ullman	
	List	Func	List	Func	List	Func	List	Func
12345678	10	0	5	0	17	18	1	2
	2	1	1	1	19	20	0	0
	1	1	5	4	19	20	0	0
	1	0	3	2	20	19	0	1
	1	1	1	1	20	20	0	1
	1	1	4	1	19	20	0	1
87654321	1	1	2	3	20	20	0	1
	1	0	3	3	19	19	0	1
	1	0	2	1	20	19	0	1
	6	0	3	1	20	20	1	1
	1	0	1	1	18	20	0	0
	0	0	2	3	20	19	0	1
777882234	1	1	1	2	20	20	0	0
	2	2	2	4	19	20	0	1
	10	1	4	2	18	20	0	1
	0	0	3	3	19	20	0	0
	3	0	3	2	19	19	0	1
	1	1	2	2	20	20	0	2
15376482	2	0	3	0	19	19	0	1
Summation :	55	11	54	38	380	392	2	18

TABLE 5
Nonlinear Function Results

Seed	Orig		Fifo		Steep		Ullman	
	List	Func	List	Func	List	Func	List	Func
12345678	3	0	3	4	12	18	5	0
	1	1	2	2	18	19	2	1
	6	0	4	2	11	15	0	3
	4	1	4	2	15	18	0	3
	5	0	5	3	15	18	2	0
87654321	2	0	2	2	15	19	3	0
	4	1	2	0	15	19	0	2
	3	0	3	2	16	18	1	1
	4	0	2	0	17	18	0	2
	4	1	5	11	8	11	5	1
777882234	2	0	4	2	13	17	2	1
	4	0	4	1	15	18	0	1
	3	1	2	0	14	18	1	2
	7	2	1	3	12	16	1	3
	4	0	5	7	9	16	4	0
15376482	1	0	1	2	16	19	4	0
	3	0	3	1	18	20	0	0
	4	1	6	2	13	17	0	3
	2	1	3	2	17	18	0	3
Summation :	69	11	63	50	286	350	30	27

VII. CONCLUSIONS

The effect of the four selection methods: Last In First Out, First In First Out, Steepest Descent, and Ullman's Depth First Search was investigated with regard to the convergence rate of Kildall's program flow graph analysis algorithm. The overall result was that the steepest descent method required the smallest number of applications. One question which arises is how to implement the idea of the steepest descent for a real program? The amount of computations to determine the "smallest optimizing pool" might be more expensive with regard to execution time or storage to process the algorithm than the effort to optimize by the other methods. This possible disadvantage can be overcome by the following. When computing the meet operation the size value of the pool can be computed too. This size value has to be stored for later use and will occupy additional memory space. Therefore, if a small number of applications of the meet or optimizing functions is required, the steepest descent method is most efficient, if an easy implementation is required, the first in first out method will be more easy to apply.

The graphs investigated in these simulation runs varied in the number of nodes, the number of levels, and the number of leaving arcs. The results were uniform and nearly independent of the graph type. Therefore the result of a real program investigation should not differ substantially from the results of this simulation.

APPENDIX A

The non - linear optimizing function is applicable, since the homomorphism condition is satisfied. That is, given that

$$f(n,P) = -\frac{P^2}{NX^2} + \frac{P}{NY} + NZ, \quad \text{and}$$

$$P_1 \wedge P_2 = \text{Min} (P_1, P_2)$$

then

$$f(n, P_1 \wedge P_2) = f(n, P_1) \wedge f(n, P_2).$$

This is shown to be correct in the following way:

$$f(n, P_1 \wedge P_2) = -\frac{(P_1 \wedge P_2)^2}{NX^2} + \frac{(P_1 \wedge P_2)}{NY} + NZ,$$

$$f(n, P_1) = -\frac{P_1^2}{NX^2} + \frac{P_1}{NY} + NZ, \quad \text{and}$$

$$f(n, P_2) = -\frac{P_2^2}{NX^2} + \frac{P_2}{NY} + NZ.$$

Thus

$$f((n, P_1) \wedge (n, P_2)) = \text{Min} \left(-\frac{P_1^2}{NX^2} + \frac{P_1}{NY} + NZ, \right. \\ \left. -\frac{P_2^2}{NX^2} + \frac{P_2}{NY} + NZ \right)$$

$$= \text{Min} \left(-\frac{P_1^2}{NX^2} + \frac{P_1}{NY}, -\frac{P_2^2}{NX^2} + \frac{P_2}{NY} \right) + NZ.$$

Since $P_1, P_2 \geq 0$

$$= \text{Min} \left(-\frac{P_1^2}{NX^2}, -\frac{P_2^2}{NX^2} \right) + \text{Min} \left(\frac{P_1}{NY}, \frac{P_2}{NY} \right) + NZ,$$

Since NX and NY are constants

$$= \frac{\text{Min}(P_1^2, P_2^2)}{NX^2} + \frac{\text{Min}(P_1, P_2)}{NY} + NZ$$

$$= \frac{\text{Min}(P_1, P_2)^2}{NX^2} + \frac{\text{Min}(P_1, P_2)}{NY} + NZ$$

$$= \frac{(P_1 \wedge P_2)^2}{NX^2} + \frac{(P_1 \wedge P_2)}{NY} + NZ$$

$$= f(n, P_1 \wedge P_2) \quad \text{which is the required identity.}$$

COMPUTER OUTPUT

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	10	10	10	10	10	10	10	10	10	10
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	11	12	14	13	18	14	17	20	20	17
	FUNCTALLY	11	12	14	13	18	14	17	20	20	17
FIFO	LISTTALLY	10	11	18	19	19	15	14	23	28	22
	FUNCTALLY	9	10	13	13	14	11	12	14	20	15
STEEP	LISTTALLY	10	10	16	13	17	15	14	20	21	16
	FUNCTALLY	9	10	10	10	10	10	10	10	10	10
ULLMAN	LISTTALLY	17	19	19	19	28	28	28	28	19	19
	FUNCTALLY	8	9	17	17	20	13	15	19	18	17

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	10	10	10	10	10	10	10	10	10	10
MAXCCN	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	16	18	26	20	22	23	22	18	14	16
	FUNCTALLY	16	18	26	20	22	23	22	18	14	16
FIFO	LISTTALLY	16	18	26	22	23	20	26	14	14	18
	FUNCTALLY	12	13	18	14	12	13	17	12	13	16
STEEP	LISTTALLY	13	16	26	20	22	19	22	14	14	16
	FUNCTALLY	10	10	10	10	10	10	10	10	10	10
ULLMAN	LISTTALLY	37	28	28	28	28	37	37	28	19	19
	FUNCTALLY	17	18	24	21	25	23	26	14	13	17

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	10	5	17	1
FUNCTALLY	0	0	18	2

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	20	20	20	20	20	20	20	20	20	20
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	13	23	30	66	36	22	34	42	49	49
	FUNCTALLY	13	23	30	66	36	22	34	42	49	49
FIFO	LISTTALLY	13	23	33	47	38	23	33	40	55	57
	FUNCTALLY	13	20	24	29	27	20	29	23	28	38
STEEP	LISTTALLY	13	21	26	42	34	17	23	30	35	45
	FUNCTALLY	13	17	20	20	20	16	19	20	20	20
ULLMAN	LISTTALLY	25	65	39	96	39	46	73	77	58	77
	FUNCTALLY	14	25	33	50	37	23	29	36	55	56

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	20	20	20	20	20	20	20	20	20	20
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	23	45	54	57	77	49	53	58	71	55
	FUNCTALLY	23	45	54	57	77	49	53	58	71	55
FIFO	LISTTALLY	25	40	37	52	78	38	53	56	82	77
	FUNCTALLY	23	26	26	29	40	26	34	33	45	42
STEEP	LISTTALLY	21	28	30	42	49	29	40	50	50	57
	FUNCTALLY	17	20	20	20	20	20	20	20	20	20
ULLMAN	LISTTALLY	49	77	96	96	77	58	96	77	58	58
	FUNCTALLY	23	46	43	53	70	39	53	51	55	71

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	2	1	19	0
FUNCTALLY	1	1	20	0

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	30	30	30	30	30	30	30	30	30	30
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	17	27	46	60	65	31	63	89	105	86
	FUNCTALLY	17	27	46	60	65	31	63	89	105	86
FIFO	LISTTALLY	17	25	40	41	63	28	33	53	66	74
	FUNCTALLY	17	24	30	34	44	27	30	32	38	49
STEEP	LISTTALLY	17	25	35	41	54	27	36	44	54	54
	FUNCTALLY	17	24	29	30	30	27	29	30	30	30
ULLMAN	LISTTALLY	33	47	85	88	88	53	85	117	146	117
	FUNCTALLY	18	28	40	53	57	28	40	66	80	66

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	30	30	30	30	30	30	30	30	30	30
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	59	85	136	117	89	98	106	87	140	139
	FUNCTALLY	59	85	136	117	89	98	106	87	140	139
FIFO	LISTTALLY	28	51	75	93	107	55	71	95	91	95
	FUNCTALLY	24	36	41	52	55	47	51	48	41	48
STEEP	LISTTALLY	28	37	52	56	75	39	47	61	80	78
	FUNCTALLY	24	29	30	30	30	29	30	30	30	30
ULLMAN	LISTTALLY	93	113	117	175	88	113	117	117	146	175
	FUNCTALLY	36	60	92	72	84	64	76	71	101	121

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	1	5	19	0
FUNCTALLY	1	4	20	0

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	40	40	40	40	40	40	40	40	40	40
MAXCCN	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	23	27	94	87	72	39	73	112	126	141
	FUNCTALLY	23	27	94	87	72	39	73	112	126	141
FIFO	LISTTALLY	16	27	52	66	62	27	46	81	86	118
	FUNCTALLY	16	26	43	56	44	24	39	56	49	57
STEEP	LISTTALLY	16	27	47	50	62	26	37	56	67	89
	FUNCTALLY	16	26	36	40	40	24	33	40	40	40
ULLMAN	LISTTALLY	31	51	106	157	118	70	97	118	157	196
	FUNCTALLY	15	27	48	77	70	28	48	82	113	127

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	40	40	40	40	40	40	40	40	40	40
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	62	88	123	131	142	206	107	158	149	179
	FUNCTALLY	62	88	123	131	142	206	107	158	149	179
FIFO	LISTTALLY	42	49	91	101	128	54	64	82	124	142
	FUNCTALLY	40	42	66	57	63	44	48	52	63	69
STEEP	LISTTALLY	33	44	61	75	89	45	52	72	94	97
	FUNCTALLY	31	39	40	40	40	38	38	40	40	40
ULLMAN	LISTTALLY	91	153	235	157	196	149	149	196	157	196
	FUNCTALLY	48	67	94	100	131	76	86	98	120	126

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	1	3	20	0
FUNCTALLY	0	2	19	1

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	50	50	50	50	50	50	50	50	50	50
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	16	36	53	66	161	34	92	88	106	112
	FUNCTALLY	16	36	53	66	161	34	92	88	106	112
FIFO	LISTTALLY	16	32	54	88	77	34	44	80	120	118
	FUNCTALLY	16	31	51	70	54	34	42	61	77	76
STEEP	LISTTALLY	16	31	46	62	65	31	43	65	84	97
	FUNCTALLY	16	29	43	49	50	30	39	50	50	50
ULLMAN	LISTTALLY	31	57	127	145	148	59	115	197	197	148
	FUNCTALLY	16	31	57	80	79	31	66	93	114	102

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE LINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	50	50	50	50	50	50	50	50	50	50
MAXCON	2	4	10	20	2	4	10	20	30	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	50	50	50	50	30	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	46	87	148	214	169	190	214	264	232	304
	FUNCTALLY	46	87	148	214	169	190	214	264	232	304
FIFO	LISTTALLY	51	75	96	103	54	90	109	157	149	215
	FUNCTALLY	48	65	61	64	49	66	76	84	93	108
STEEP	LISTTALLY	35	53	69	98	49	67	86	121	118	131
	FUNCTALLY	31	46	50	50	43	50	50	50	50	50
ULLMAN	LISTTALLY	121	136	246	197	127	197	246	246	246	246
	FUNCTALLY	58	78	116	112	61	91	119	176	165	186

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LCWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	1	1	20	0
FUNCTALLY	1	1	20	1

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	10	10	10	10	10	10	10	10	10	10
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	11	24	27	26	42	19	27	39	40	39
	FUNCTALLY	11	24	27	26	42	19	27	39	40	39
FIFO	LISTTALLY	13	20	18	26	46	17	22	31	44	36
	FUNCTALLY	12	15	16	15	22	14	15	20	21	22
STEEP	LISTTALLY	14	20	20	22	39	15	30	31	40	33
	FUNCTALLY	12	14	15	10	16	11	18	17	15	18
ULLMAN	LISTTALLY	25	37	46	37	37	28	37	37	37	28
	FUNCTALLY	11	23	19	26	34	15	23	32	44	35

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	10	10	10	10	10	10	10	10	10	10
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	27	29	35	46	38	32	40	35	38	48
	FUNCTALLY	27	29	35	46	38	32	40	35	38	48
FIFO	LISTTALLY	24	30	39	37	32	26	37	42	35	51
	FUNCTALLY	18	16	18	19	15	17	18	22	18	16
STEEP	LISTTALLY	20	25	24	32	27	21	27	38	42	39
	FUNCTALLY	15	17	10	16	17	10	14	17	25	20
ULLMAN	LISTTALLY	37	37	37	37	37	28	37	37	46	37
	FUNCTALLY	22	28	31	37	29	22	33	38	33	48

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LCWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	2	5	11	4
FUNCTALLY	1	5	14	1

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	20	20	20	20	20	20	20	20	20	20
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	27	27	39	37	66	31	36	72	101	89
	FUNCTALLY	27	27	39	37	66	31	36	72	101	89
FIFO	LISTTALLY	17	23	46	48	61	23	37	47	86	70
	FUNCTALLY	16	20	31	35	36	20	29	30	43	37
STEEP	LISTTALLY	17	21	43	41	52	29	31	43	61	73
	FUNCTALLY	16	16	26	21	28	23	24	21	24	32
ULLMAN	LISTTALLY	40	46	39	58	58	52	58	77	77	77
	FUNCTALLY	15	29	37	41	60	30	32	50	73	73

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	20	20	20	20	20	20	20	20	20	20
MAXCCN	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	49	59	88	74	119	60	64	72	119	110
	FUNCTALLY	49	59	88	74	119	60	64	72	119	110
FIFO	LISTTALLY	54	55	57	61	90	47	64	84	72	106
	FUNCTALLY	46	34	34	42	46	33	42	40	34	38
STEEP	LISTTALLY	43	58	56	68	84	42	60	61	77	82
	FUNCTALLY	27	34	34	38	28	25	37	24	27	30
ULLMAN	LISTTALLY	73	77	96	96	77	77	96	58	77	77
	FUNCTALLY	43	57	67	62	76	44	64	64	51	94

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	2	6	10	4
FUNCTALLY	0	3	18	1

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	30	30	30	30	30	30	30	30	30	30
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	19	49	51	81	87	33	52	66	132	137
	FUNCTALLY	19	49	51	81	87	33	52	66	132	137
FIFO	LISTTALLY	19	37	67	83	82	31	49	65	99	108
	FUNCTALLY	19	35	52	52	56	29	42	47	53	63
STEEP	LISTTALLY	19	33	52	71	67	34	53	68	87	104
	FUNCTALLY	19	27	34	43	34	29	38	42	45	42
ULLMAN	LISTTALLY	37	70	85	88	88	58	105	88	146	117
	FUNCTALLY	19	36	54	85	87	30	48	67	97	109

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	30	30	30	30	30	30	30	30	30	30
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	54	90	101	132	116	78	82	120	144	155
	FUNCTALLY	54	90	101	132	116	78	82	120	144	155
FIFO	LISTTALLY	47	61	82	122	109	60	82	99	145	151
	FUNCTALLY	38	43	44	67	63	49	52	52	62	57
STEEP	LISTTALLY	53	64	65	106	95	61	73	96	99	122
	FUNCTALLY	43	38	37	43	42	38	41	44	32	43
ULLMAN	LISTTALLY	70	117	88	117	88	117	117	117	117	117
	FUNCTALLY	37	70	79	115	94	60	85	103	107	143

THE FOLLOWING LIST REPRESENTS THE NUMBER OF TIMES THE CORRESPONDING METHOD USED THE LOWEST OR SAME NUMBER OF APPLICATIONS DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	2	7	11	2
FUNCTALLY	1	2	19	2

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	40	40	40	40	40	40	40	40	40	40
MAXCCN	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLLWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	21	38	82	84	125	45	58	88	144	176
	FUNCTALLY	21	38	82	84	125	45	58	88	144	176
FIFO	LISTTALLY	21	40	84	86	115	49	63	86	140	137
	FUNCTALLY	21	38	68	71	72	48	56	61	80	78
STEEP	LISTTALLY	21	39	73	89	96	42	62	85	113	121
	FUNCTALLY	20	37	53	67	49	36	48	58	60	58
ULLMAN	LISTTALLY	49	82	100	157	118	88	109	157	157	157
	FUNCTALLY	19	35	71	90	111	48	54	90	121	124

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	40	40	40	40	40	40	40	40	40	40
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	30	50	50	50	50	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	57	74	104	135	193	58	92	139	172	185
	FUNCTALLY	57	74	104	135	193	58	92	139	172	185
FIFO	LISTTALLY	49	86	105	131	152	55	95	136	149	145
	FUNCTALLY	42	67	69	74	74	46	66	72	73	73
STEEP	LISTTALLY	53	69	96	120	134	58	92	109	158	141
	FUNCTALLY	43	45	49	53	56	49	62	51	59	52
ULLMAN	LISTTALLY	91	149	118	157	157	106	157	157	157	157
	FUNCTALLY	46	80	95	120	147	56	85	124	170	140

THE FOLLOWING LIST REPRESENTS THE NUMBER OF TIMES THE CORRESPONDING METHOD USED THE LOWEST OR SAME NUMBER OF APPLICATIONS DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	5	4	14	0
FUNCTALLY	0	2	16	2

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	1	2	3	4	5	6	7	8	9	10
NMNODE	50	50	50	50	50	50	50	50	50	50
MAXCON	2	4	10	20	30	2	4	10	20	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	10	10	10	10	10	20	20	20	20	20

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	21	35	68	92	145	38	100	165	156	187
	FUNCTALLY	21	35	68	92	145	38	100	165	156	187
FIFO	LISTTALLY	21	32	69	72	113	45	77	116	143	181
	FUNCTALLY	20	30	61	57	73	42	73	95	101	99
STEEP	LISTTALLY	21	36	69	83	102	38	75	107	124	146
	FUNCTALLY	20	34	61	60	54	32	65	74	65	73
ULLMAN	LISTTALLY	69	49	136	139	197	79	127	193	193	197
	FUNCTALLY	20	30	63	81	115	38	68	116	137	165

STATISTICAL SUMMARY

STARTSEED FOR THIS RUN = 12345678

THE NONLINEAR OPTIMIZING FUNCTION WAS USED

RUN	11	12	13	14	15	16	17	18	19	20
NMNODE	50	50	50	50	50	50	50	50	50	50
MAXCON	2	4	10	20	2	4	10	20	30	30
MALGTH	100	100	100	100	100	100	100	100	100	100
MAXLVL	30	30	30	30	50	50	50	50	30	50

THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.

LIFO	LISTTALLY	59	90	160	184	78	131	179	209	194	231
	FUNCTALLY	59	90	160	184	78	131	179	209	194	231
FIFO	LISTTALLY	55	85	137	169	89	137	150	185	174	178
	FUNCTALLY	49	72	99	88	77	103	85	96	83	81
STEEP	LISTTALLY	52	74	115	142	63	120	129	154	146	173
	FUNCTALLY	48	56	60	64	53	82	60	59	57	65
ULLMAN	LISTTALLY	106	177	197	197	133	193	197	197	197	246
	FUNCTALLY	51	93	141	166	67	138	141	188	168	159

THE FOLLOWING LIST REPRESENTS THE NUMBER
OF TIMES THE CORRESPONDING METHOD USED THE
LOWEST OR SAME NUMBER OF APPLICATIONS
DURING THE LAST 20 RUNS.

	ORIG	FIFO	STEEP	ULLMAN
LISTTALLY	3	3	17	0
FUNCTALLY	0	4	18	2


```

LUK000020
LUK000030
LUK000040
LUK000050
LUK000060
LUK000070
LUK000080
LUK000090
LUK000100
LUK000110
LUK000120
LUK000130
LUK000140
LUK000150
LUK000160
LUK000170
LUK000180
LUK000190
LUK000200
LUK000210
LUK000220
LUK000230
LUK000240
LUK000250
LUK000260
LUK000270
LUK000280
LUK000290
LUK000300
LUK000310
LUK000320
LUK000330
LUK000340
LUK000350
LUK000360
LUK000370
LUK000380
LUK000390
LUK000400
LUK000410
LUK000420
LUK000430
LUK000440
LUK000450
LUK000460
LUK000470
LUK000480
LUK000490

C O M P U T E R   P R O G R A M
      F O R
S I M U L A T I O N   M O D E L

*****
THIS PROGRAM IS THE FORTRAN IMPLEMENTATION OF THE ALGORITHM Q OUT
OF PROF. G. KILDAL, S
GLOBAL EXPRESSION OPTIMISATION DURING COMPILATION   PAGE 40
REF. 6
*****

IN KNUTH NOTATION :
      Q1 INITIALIZE ?
      Q2 TERMINATE ?
      Q3 SELECT A NODE
      Q4 TRAVERSE ?
      Q5 SET STATE
      Q5 LOOP

THE MOTIVATION TO WRITE THIS PROGRAM IS TO TRY SEVERAL
MODIFICATION OF THE SELECT STEP TO OPTIMIZE THE TRAVERSE STEP.

EXPLANATION OF ABBREVIATIONS AND NAMES

NSTART = START NODE
INTVSM = SUM OF INTERVALS UP TO THE CORRESPONDING NODE
INTVAL = DISTANCE BETWEEN TWO NODES ALONG ONE ARC
NGHLST = NEIGHBORLIST OR INVESTIGATION LIST "L"
NGHBR = NEIGHBOR NODE BEING PROCESSED
NEWNGH = NODE BEING ENTERED TO THE INVESTIGATION LIST

*****
IMPLICIT INTEGER (0)
1 DIMENSION NETWORK($), RNCON(400), LEVEL(100), INTVSM(101),
2 NSMARRY(10,20), ITOUCH(101), IFETCH(101),
3 MARCON(100), MALGTH(100), MARLVL(100), NORDER(100), ORDLST(100),
COMMON NETWORK, RNCON, LEVEL, INTVSM, NGHLST, ISTART, NGHBR,
1 NMNODE, NEWNGH, RNROOT, I, ITOUCH, NSAVE, $NOPRT, NANODE,
2 MARCON, MALGTH, MARLVL, IDATA, NORDER, NUMNDE,
3 ORDLST, $LIN, IFETCH

THE FRAME LOOP "IDATA" WILL PROVIDE FOR SEVERAL DISTINCT

```

CC

CC


```

C          PROGRAM GRAPHS. TO AVOID REPETITION OF THE RANDOM NUMBERS
        ISTART = 12345678
        QSTART = ISTART
        $LIN = .TRUE.
        $NOPRT = .TRUE.
        DO 6000 LUKA = 1,5
        DO 4 MN = 1,20
        NANUDE(MN) = 0
        MARCON(MN) = 0
        MALGTH(MN) = 0
        MARVLV(MN) = 0
        CONTINUE
        DO 5 NN = 1,10
        IWIN(NN) = 0
        DO 5 MN = 1,20
        NSMAY(NM,MN) = 0
        CONTINUE
        DO 5500 IDATA = 1, 20
        CALL DATA

        THE FOLLOWING LOOP "ISELCT" WILL PROVIDE FOR THE CONTROL-
        VALUE FOR THE COMPUTED GO TO. THAT IS THE SAME GRAPH
        AND THE SAME START NODE ARE USED FOR DIFFERENT ROUTINES
        SELECT# AND ENTER#

        DO 5000 ISELCT= 1,4

        STEP 1 OF THE ALGORITHM " INITIALIZE"
        *****

        DO 10 KILL = 1,101
        INTVSM(KILL) = 99999
        NGHLST(KILL) = 0
        ITOUCH(KILL) = 0
        IFETCH(KILL) = 0
        CONTINUE
        NSTART = 1
        INTVSM(NSTART) = 1
        IF($LIN) INTVSM(1) = 0
        NGHLST(1) = NSTART
        NSAVE = 1

        STEP 2 OF THE ALGORITHM TERMINATE ?
        *****

        IF (NGHLST(1).EQ.0) GO TO 200

```



```

116 GC TO 150
    CALL ENTER1
118 GC TO 150
150 GC TO 200
    CONTINUE
    GU TO 100
C
C *****
C FINAL STEP TO GET THE RESULT AND THE STATISTICS
C *****
200 ISUM = 1
    LSUM = 0
    DO 60 I = 1,100
        ISUM = ISUM + IFETCH(I)
        LSUM = LSUM + IFETCH(I)
        CONTINUE
        IF($NQPRT) GO TO 4900
        WRITE(6,1000) IDATA, ISELCT
        WRITE(6,1001) (I,I=1,20)
        WRITE(6,1002) (IFETCH(I),I=1,20)
        WRITE(6,1006) ISUM
        WRITE(6,1017) (IFETCH(I),I = 1,20)
        WRITE(6,1018) LSUM
        DO 4800 I = 1,NMNODE
            WRITE(6,1016) I , INTVSM(I)
            CONTINUE
        NSMRY(I,ISELCT,IDATA) = ISUM
        NSMRY(I,ISELCT + 5,IDATA) = LSUM
        CONTINUE
        LSTVAL = MINO(NSMRY(1,IDATA),NSMRY(2,IDATA),NSMRY(3,IDATA) ,
        LSTVAL(4,IDATA) )
        LEUVAL = MINO(NSMRY(6,IDATA),NSMRY(7,IDATA),NSMRY(8,IDATA) ,
        LSTVAL(9,IDATA) )
        DO 4950 LS = 1,4
            IF(LSTVAL.EQ.NSMRY(LS,IDATA)) IWIN(LS) = IWIN(LS) + 1
            IF(LEUVAL.EQ.NSMRY(LS+5,IDATA)) IWIN(LS+5)=IWIN(LS+5) +1
            CONTINUE
        CONTINUE
        I1 = 1
        I2 = 10
        WRITE(6,1005) QSTART
        WRITE(6,1020) WRITE(6,1021)
        IF($LIN) WRITE(6,1022)
        IF(.NOT.$LIN) WRITE(6,1022)
        WRITE(6,1007) (I,I=11,I2)
        WRITE(6,1011) (NANGDE(I),I=11,I2)

```

```

LUK01460
LUK01470
LUK01480
LUK01490
LUK01500
LUK01510
LUK01520
LUK01530
LUK01540
LUK01550
LUK01560
LUK01570
LUK01580
LUK01590
LUK01600
LUK01610
LUK01620
LUK01630
LUK01640
LUK01650
LUK01660
LUK01670
LUK01680
LUK01690
LUK01700
LUK01710
LUK01720
LUK01730
LUK01740
LUK01750
LUK01760
LUK01770
LUK01780
LUK01790
LUK01800
LUK01810
LUK01820
LUK01830
LUK01840
LUK01850
LUK01860
LUK01870
LUK01880
LUK01890
LUK01900
LUK01910
LUK01920
LUK01930

```


1026	FORMAT('0',15X,'FUNCTIONALLY',10X,I4,I4X,I4,I4X,I4)	LUK02420
1027	FORMAT('0',15X,'OF TIMES THE CORRESPONDING METHOD USED THE')	LUK02430
1028	FORMAT('0',15X,'THE FOLLOWING NUMBERS ARE THE COUNTER CONTENTS.')	LUK02440
1029	FORMAT('0',15X,'LOWEST OR SAME NUMBER OF APPLICATIONS.')	LUK02450
1030	FORMAT('0',15X,'DURING THE LAST 20 RUNS.')	LUK02460
6000	CONTINUE	LUK02470
	IF(.NOT.\$LIN) GO TO 6002	LUK02480
	\$LIN = .FALSE.	LUK02490
	GO TO 6001	LUK02500
6002	WRITE(6,6003)	LUK02510
6003	FORMAT('1',,')	LUK02520
	STOP	LUK02530
	END	LUK02540


```

C
C
C
C
C
SUBROUTINE SELECT1
THIS PROCEDURE SELECTS THE FIRST ONE OF
THE LIST TO BE THE NEXT SELECTED NCDE. THEN ALL OTHERS ARE
CHANGED TO THE LOWER ARRAYBOX
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWORK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMARRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 MARCCN(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLS(2500)
COMMON NETWORK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBOR,
1 NMNDE,NEWNG8,RNROOT,I,ITOUCH,NSAVE,$NCPRT,NANODE,
2 MARCON,MALGTH,MARLVL,IData,NORDER,NUMNDE,
3 ORDLST,$LIN,IFETCH
NGHBOR = NGHLS(1)
IF($NCPRT) GO TO 9
WRITE(6,1000) NGHBOR
FORMAT(10,16)
DO 10 ISEL=1,NMNDE
  NGHLS(ISEL) = NGHLS(ISEL + 1)
  IF(NGHLS(ISEL).EQ.0) RETURN
CONTINUE
RETURN
END
1000
9
10

```

```

LUK02570
LUK02580
LUK02590
LUK02600
LUK02610
LUK02620
LUK02630
LUK02640
LUK02650
LUK02660
LUK02670
LUK02680
LUK02690
LUK02700
LUK02710
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LUK02750
LUK02760
LUK02770
LUK02780
LUK02790
LUK02800
LUK02810
LUK02820

```



```

C
C
SUBROUTINE SELCT2
THIS ROUTINE WILL SELECT THAT NODE WHICH WAS LAST ENTERED
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWRK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 MARCON(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLST(250)
COMMON NETWRK,RNCONT,LEVEL,INTVSM,NGHLST,ISTART,NGHBOR,
1 NMNOCDE,NEWNGB,RNRDOOF,I,ITOUCH,NSAVE,$NGPRT,NANODE,
2 MARCON,MALGTH,MARLVL,IData,NURDER,NUMNDE,
3 ORDLST,$LIN,IFETCH
NGHBOR = NGHLST(NSAVE)
IF($NGPRT) GO TO 9
WRITE(6,1000)NGHBOR
FORMAT(1,1,SELECTED',I6)
NGHLST(NSAVE) = 0
1 NSAVE = NSAVE - 1
2 IF(NSAVE.EQ.0)NSAVE = 1
3 RETURN
END
1000
9
C

```

```

LUK02850
LUK02860
LUK02870
LUK02880
LUK02890
LUK02900
LUK02910
LUK02920
LUK02930
LUK02940
LUK02950
LUK02960
LUK02970
LUK02980
LUK02990
LUK03000
LUK03010
LUK03020
LUK03030
LUK03040
LUK03050
LUK03060
LUK03070
LUK03080

```



```

C C C C C
SUBROUTINE ENTER1
THIS PROCEDURE WILL ADD THE NEW NEIGHBOR TO THE END OF THE ARRAY
IF IT IS NOT ALREADY IN THE ARRAY
FOR STATISTIC REASONS WRITE THE NEIGHLIST AND THE NODE,
WHICH IS TO BE ENTERED
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWORK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMARRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 MARCCN(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLS(2500)
COMMON NETWORK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBR,
1 NMNODE,NEWNGB,RNROOT,I,ITOUCH,NSAVE,$NOPRT,NANGDE,
2 MARCCN,MALGTH,MARLVL,DATA,NORDER,NUMNDE,
3 ORDLST,$LIN,IFETCH
C C
DO 10 IENT = 1,NMNODE
IF(NGHLS(IENT).EQ.0) NGHLS(IENT) = NEWNGB
IF(NGHLS(IENT).EQ.NEWNGB) GO TO 20
CONTINUE
IF($NOPRT) GO TO 9
WRITE(6,1000)(NGHLS(I),I=1,20)
FORMAT(1,1,L=1,20I4)
RETURN
END
10
20
1000
9

```

```

LUK03450
LUK03460
LUK03470
LUK03480
LUK03490
LUK03500
LUK03510
LUK03520
LUK03530
LUK03540
LUK03550
LUK03560
LUK03570
LUK03580
LUK03590
LUK03600
LUK03610
LUK03620
LUK03630
LUK03640
LUK03650
LUK03660
LUK03670
LUK03680
LUK03690
LUK03700
LUK03710
LUK03720

```



```

C
C
C
SUBROUTINE ENTER3
THIS ROUTINE WILL BUILD A STACK OF NODES FOR THE SELECT STEP
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWRK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 MARCON(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLS(2500)
COMMON NETWRK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBCR,
1 MMNODE,NEWNGB,RNROOT,I,ITOUCH,NSAVE,$NOPRT,NANODE,
2 MARCON,MALGTH,MARLVL,IData,NORDER,NUMNDE,
3 ORDLST,$LIN,IFETCH
IF(NSAVE.NE.1)GO TO 10
IF(NGHLS(NSAVE).NE.0) GO TO 10
NSAVE = 0
NSAVE = NSAVE + 1
NGHLS(NSAVE) = NEWNGB
IF($NOPRT) GO TO 9
WRITE(6,1000)(NGHLS(I),I=1,20)
FORMAT(' ',L = ',20I4)
RETURN
END
10
1000
9

```

```

LUK03750
LUK03760
LUK03770
LUK03780
LUK03790
LUK03800
LUK03810
LUK03820
LUK03830
LUK03840
LUK03850
LUK03860
LUK03870
LUK03880
LUK03890
LUK03900
LUK03910
LUK03920
LUK03930
LUK03940
LUK03950
LUK03960
LUK03970
LUK03980

```



```

SUBROUTINE DATA
THIS PROGRAM CONSTRUCTS A PROGRAM FLOW GRAPH IN THE FOLLOWING
WAY;
1  START WITH THE NODE "1" AS THE ENTRY.
2  GENERATE FOR EACH OUTGOING ARC THE INGOING NODE AND THE
   DISTANCES AND TAKE ONE ARC ONLY.
3  TO AVOID A DISCONNECTED GRAPH PICK BY LLRANDOM ONE OF THE
   INGOING NODES OF THE LAST LEVEL AS THE NEW ROOT FOR THE
   NEXT LEVEL.
4  GO TO 2

THE OUTPUT OF THIS ROUTINE IS THE GRAPH IN MATRIX FORM AND THE
INGOING NODES OF THE LAST LEVEL, AVAILABLE IN COMMON
TO SIMULATE DIFFERENT GRAPHS CHANGE:
   THE MAXIMAL NUMBER OF ARCS
   THE MAXIMAL NUMBER OF LEVELS
   THE MAXIMAL NUMBER OF LENGTH BETWEEN THE NODES

IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWRK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
          NSMRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
          MARCON(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
          NGHLS(2500)
COMMON NETWRK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBOR,
       NMNODE,NEWNGB,RNROOF,I,ITOUCH,NSAVE,$NOPRT,NANODE,
       MARCON,MALGTH,MARLVL,IDATA,NORDER,NUMNDE,
       ORDLST,$LIN,IFETCH
*****
DECLARATION OF VARIABLES
NMNODE = NUMBER OF NODES IN THE NETWORK MAX = 60
MAXCON = MAXIMAL NUMBER OF OUTGOING ARCS.
         LIMITED TO 60 ARCS DUE TO RANDOMNUMBERARRAY
RNCONT = RANDOMNUMBER FOR LLRANDOM
ISTART = STARTVALUE FOR CONNECTIONS
NMCON = NUMBER OF CONNECTIONS
MALGTH = MAXIMAL LENGTH OF THE INTERVALL
NETWRK = MATRIX FOR THE GENERATED INTERVALLLENGTH
RNROOF = MATRIX FOR THE NEXT LEVEL
MAXLVL = MAXIMAL ROOT FOR THE LEVELS
LEVEL = ARRAY FOR THE END NODES OF THE LEVEL
LVLCONT = LEVELCOUNTER
*****

```

CCCCCCCCCCCCCCCCCCCC

CCCCCCCCCCCCCCCCCCCC


```

      INTVAL = RNCONT(ICOUNT + NJ) * MXLGTH + 0.5
      IF (INTVAL.EQ.0) INTVAL = 1
      NETWRK(NDEOUT,NDEIN,NJ) = NETWRK(NDEOUT,NDEIN,NJ)+INTVAL
      CCNTINUE
      I = I + 1
      LEVEL(I) = NDEIN
      CCNTINUE
      CCNTINUE
      *****
      PRINT THE NETWORK IN MATRIX FORM. IF THE NUMBER OF NODES
      IS LESS THAN THE PREDEFINED ONE THE LAST COLUMNS ARE
      FILLED WITH ZEROS
      IF($NQPRT) GO TO 615
      DO 610 NJ = 1, 3
      WRITE(6,1010)( I3, I3 = 1,20)
      DO 600 I4 = 1,MNODE
      WRITE(6,1011) I4,(NETWRK(I4,I5,NJ), I5 = 1,20)
      CCNTINUE
      CCNTINUE
      *****
      FORMAT(4I4)
      FFORMAT('O','NODES',20I4/)
      FFORMAT(' ',2X,I4,2X,20I4)
      RETURN
      END

```



```

C
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SUBROUTINE ULLMAN
THIS ROUTINE IS THE IMPLEMENTATION OF THE
DEPTH FIRST ALGORITHM D
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWORK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 MARCCN(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLS(2500)
COMMON NETWORK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBR,
1 NMNCDE,NEWNGB,RNRGOT,I,ITOUCH,NSAVE,$NOPRT,NANODE,
2 MARCCN,MALGTH,MARLVL,IData,NORDER,NUMNDE,
3 ORDLST,$LIN,IFETCH
C
CALL RECDR
IF ($NOPRT) GO TO 5
DO 6 I = 1,NMNCDE
WRITE(6,1010) I,NORDER(I)
1010 FORMAT(1,1010) I,NORDER(I)
CONTINUE
C
STEP ONE
DO 10 J = 2,NUMNDE
NSCN = ORDLST(J)
ITOUCH(NSCN) = 1
DO 20 JPRE = 1,NMNCDE
IF(JPRE.EQ.NSCN) GO TO 20
IF(NETWK(JPRE,NSCN,1).EQ.0) GO TO 20
IF(NORDER(JPRE).GT.J) GO TO 20
NX = NETWK(JPRE,NSCN,1)
NY = NETWK(JPRE,NSCN,2)
NZ = NETWK(JPRE,NSCN,3)
C
OPTIMIZING FNCTION
IF($LIN) INTVAL = INTVSM(JPRE) + NX
IF(.NOT.$LIN)
1 INTVAL=FLOAT(INTVSM(JPRE)**2)/NX**2+FLOAT(INTVSM(JPRE))/NY + NZ
C
C
MEETFUNCTION
IF(INTVSM(NSCN).LE.INTVAL)GO TO 20
C
INTVSM(NSCN) = INTVAL
IFETCH(NSCN) = IFETCH(NSCN) +1
CONTINUE
20

```


10	CCONTINUE	LUK05740
C		LUK05750
C		LUK05760
C		LUK05770
C		LUK05780
C		LUK05790
	STEP TWO	LUK05800
	\$CHANGE = .TRUE.	LUK05810
30	NULCNT = 1	LUK05820
	IF(\$CHANGE) GO TO 40	LUK05830
1000	IF(.NOT.\$NOPRT) WRITE(6,1000) NULCNT	LUK05840
	FORMAT('0',THE NUMBER OF ITERATION IS ',I6)	LUK05850
	RETURN	LUK05860
40	\$CHANGE=.FALSE.	LUK05870
	NULCNT = NULCNT + 1	LUK05880
	DO 50 J = 2,NUMNDE	LUK05890
	NSON = ORDLST(J)	LUK05900
	ITOUCH(NSON) = ITOUCH(NSON) + 1	LUK05910
	DC 60 JPRE = 1,NMNODE	LUK05920
	IF(JPRE.EQ.NSON) GO TO 60	LUK05930
	IF(NETWRK(JPRE,NSON,1).EQ.0) GO TO 60	LUK05940
	NX = NETWRK(JPRE,NSON,1)	LUK05950
	NY = NETWRK(JPRE,NSON,2)	LUK05960
	NZ = NETWRK(JPRE,NSON,3)	LUK05970
C	OPTIMIZING FNCNTION	LUK05980
C	IF(\$LIN) INTVAL = INTVSM(JPRE) + NX	LUK05990
	IF(.NOT.\$LIN)	LUK06000
	1)INTVAL=FLOAT(INTVSM(JPRE)**2)/NX**2+FLOAT(INTVSM(JPRE))/NY + NZ	LUK06010
C		LUK06020
C	MEETFUNCTIION	LUK06030
C	IF(INTVSM(NSON).LE.INTVAL)GO TO 60	LUK06040
C		LUK06050
	INTVSM(NSON) = INTVAL	LUK06060
	IFETCH(NSON) = IFETCH(NSON) +1	LUK06070
	\$CHANGE = .TRUE.	LUK06080
60	CCONTINUE	LUK06090
50	GO TO 30	LUK06100
	END	LUK06110
		LUK06120
		LUK06130


```

C
C
C
SUBROUTINE REORDR
THIS ROUTINE WILL DETERMINE THE ORDER OF THE NODES
DUE TO THE ALGORITHM D FOR DFST FLOWGRAPH
L
IMPLICIT INTEGER (0)
IMPLICIT LOGICAL ($)
DIMENSION NETWORK(100,100,3),RNCONT(400),LEVEL(100),INTVSM(101),
1 NSMRY(10,20),ITOUCH(101),NANODE(100),IFETCH(101),
2 NSMRY(100),MALGTH(100),MARLVL(100),NORDER(100),ORDLST(100),
3 NGHLS(2500)
COMMON NETWORK,RNCONT,LEVEL,INTVSM,NGHLS,ISTART,NGHBR,
1 NMNODE,NEWGB,RNROOT,I,ITOUCH,NSAVE,$NOPRT,NANODE,
2 ORDLST,$LIN,IFETCH
3 ORDLST,THE ORDER ATTRIBUTE
ZERO OUT THE ORDER ATTRIBUTE
DO 10 IORD = 1,NMNODE
NORDER(IORD) = 0
ORDLST(IORD) = 0
CONTINUE
10 NCRDER(1) = 1
C DETERMINE THE NUMBER OF NODES IN THIS NETWORK
NMNDE = 0
DO 20 NUM1 = 1,NMNODE
NSUM = 0
DO 30 NUM2 = 1,NMNODE
NSUM = NSUM + NETWORK(NUM1,NUM2,1)+NETWORK(NUM2,NUM1,1)
30 CONTINUE
20 IF(NSUM.NE.0)NMNDE = NMNDE + 1
CONTINUE
IN = NMNDE
NSAVE = 1
NPRED = 1
NMNDE = NSAVE
DO 40 IPLUS = 1, NMNODE
TO GET THE RIGHT SON
IMIN = NMNODE - IPLUS + 1
IF(NETWK(NPRED,IMIN,1).EQ.0) GO TO 40
IF(NORDER(IMIN).GT.0) GO TO 40
IF(NORDER(IMIN).LT.0) GO TO 40
NCRDER(IMIN) = -10
NEWGB = IMIN
CALL ENTER3
NPRED = NGHLS(NSAVE)
GO TO 60
CONTINUE
NCRDER(NPRED) = NMNDE
ORDLST(NMNDE) = NPRED
NMNDE = NMNDE - 1
40

```

LUK06160
 LUK06170
 LUK06180
 LUK06190
 LUK06200
 LUK06210
 LUK06220
 LUK06230
 LUK06240
 LUK06250
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 LUK06270
 LUK06280
 LUK06290
 LUK06300
 LUK06310
 LUK06320
 LUK06330
 LUK06340
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 LUK06360
 LUK06370
 LUK06380
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 LUK06570
 LUK06580
 LUK06590
 LUK06600
 LUK06610
 LUK06620
 LUK06630


```

70      NSAVE = NSAVE - 1
      IF (NPRE.D.EQ.1) GO TO 70
      NPRE.D = NGHLST(NSAVE)
      GO TO 60
1000    IF (NUMNDE.EQ.0) GO TO 80
      WRITE(6,1000)
      FORMAT('  ERROR IN REORDERING  ')
      RETURN
80      NUMNDE = IN
      RETURN
      END

```

```

LUK06640
LUK06650
LUK06660
LUK06670
LUK06680
LUK06690
LUK06700
LUK06710
LUK06720
LUK06730
LUK06740

```


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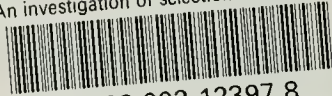
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